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**Use of spatial analyses for global characterization of
wheat-based production systems**

D. P. HODSON^{1*} AND J. W. WHITE^{1,2}

¹ CIMMYT, Int. Apdo. Postal 6-641, 06600 Mexico, DF, Mexico

² US Arid Land Agricultural Research Center, USDA-ARS, Maricopa, AZ, USA

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SUMMARY

CIMMYT (International Maize and Wheat Improvement Centre) and other research groups within the Consultative Group for International Agricultural Research (CGIAR) have made major contributions to agricultural development, e.g. underpinning the ‘green revolution’, but it is unlikely they will continue making such far-reaching contributions without the ability to collect, analyse and assimilate large amounts of spatially orientated agronomic and climatic data. Increasingly, application of modern tools and technologies are crucial elements in order to support and enhance the effectiveness of international agricultural research. Bread and durum wheats (*Triticum aestivum* and *Triticum durum*) occupy an estimated 200 million ha globally, are grown from sea level to over 3500 m asl, and from the equator to latitudes above 60° N in Canada, Europe, and Asia. For organizations like CIMMYT, which seek to improve wheat production in the developing world, understanding the geographic context of wheat production is crucial for priority setting, promoting collaboration, and targeting germplasm or management practices to specific environments. Increasingly important is forecasting how the environments, and their associated biotic and abiotic stress patterns, shift with changing climate patterns. There is also a growing need to classify production environments by combining biophysical criteria with socio-economic factors. Geospatial technologies, especially geographic information systems (GIS), are playing a role in each of these areas, and spatial analysis provides unique insights. Use of GIS to characterize wheat production environments is described, drawing from examples at CIMMYT. Since the 1980s, the CIMMYT wheat programme has classified production regions into mega-environments (MEs) based on climatic, edaphic, and biotic constraints. Advances in spatially disaggregated datasets and GIS tools allow MEs to be characterized and mapped in a much more quantitative manner. Parallel advances are improving characterizations of the actual (v. potential) distribution of major crops, including wheat. The combination of improved crop distribution data and key biophysical data at high spatial resolutions also permits exploring scenarios for disease epidemics, as illustrated for the stem rust race Ug99. Availability of spatial data describing future climate conditions may provide insights into potential changes in wheat production environments in the coming decades. There is a pressing need to advance beyond static definitions of environments and incorporate temporal aspects to define locations or regions in terms of probability or frequency of occurrence of different environment types. Increased availability of near real-time daily weather data derived from remote sensing should further improve characterization of environments, as well as permit regional-scale modelling of dynamic processes such as disease progression or crop water status.

* To whom all correspondence should be addressed. Email: d.hodson@cgiar.org

INTRODUCTION

Geospatial technologies, principally geographic information systems (GIS) and remote sensing, are finding applications in an ever-increasing range of thematic areas, from business strategies (e.g. Thomas & Ospina 2004) to defence (ESRI 2006) and health (e.g. Clarke *et al.* 1996) to conservation planning (e.g. Steklis *et al.* 2005). These technologies have emerged over the last 3 decades through a merger of fields such as computer science and image processing with more traditional disciplines such as cartography and geography. Many definitions exist for GIS, but that provided by a large commercial GIS software and data vendor, ESRI (Redlands, CA), is particularly relevant: 'GIS is a computer technology that uses a geographic information system as an analytic framework for managing and integrating data; solving a problem; or understanding a past, present, or future situation. GIS is, therefore, about modelling and mapping the world for better decision making.' Aspects of these technologies have become familiar components of our daily lives through popular applications such as Google EarthTM and MapQuestTM.

In agriculture, particularly within developed countries of the Organisation for Economic Co-operation and Development (OECD), attention has tended to focus on precision farming applications, with a whole industry developing around the use of remotely-sensed imagery, GIS, and Global Positioning Systems (GPS) to optimize management of spatial variability at the farm or plot level (e.g. Whelan & McBratney 2000). However, within development arenas, geospatial technologies find applications that extend far beyond micro-level, precision farming. White *et al.* (2002) highlighted potential applications in agriculture, natural resources management and rural development. Examination of activities of major institutions involved with international agriculture and development, e.g. FAO, Consultative Group for International Agricultural Research (CGIAR), World Bank, and USAID-FEWS Net, reveals that geospatial technologies are being applied in diverse and innovative ways to enhance knowledge and improve decision-making. Examples include the remote sensing products that now form the backbone of famine early warning systems (see <http://www.fews.net/>) and small-area estimation poverty maps that are guiding policy and development decisions (Elbers *et al.* 2004). In addition, global spatial data generation and sharing initiatives are transforming opportunities for spatial analysis in historically data-sparse regions, e.g. 90 m SRTM digital elevation data (CGIAR Consortium for Spatial Information, <http://srtm.csi.cgiar.org/>, WorldCLIM (Hijmans *et al.* 2005) and GeoNetwork (FAO 2006)). This widespread use of GIS is driven by increasing availability of geospatial data, rapid advances in software and hardware capabilities,

and greater awareness among researchers of how a geospatial perspective can enhance their research.

International agricultural research centres were early adopters of geospatial technologies. Pioneering activities date to the early 1980s at centres such as CIAT (International Centre for Tropical Agriculture, based in Colombia), where computer-based analyses and mapping were used to characterize cropping systems and germplasm distributions (Carter 1987). All 15 centres within the CGIAR network now employ geospatial approaches.

CIMMYT (International Maize and Wheat Improvement Centre) has a global mandate to improve and enhance wheat and maize-based farming systems in developing countries. For wheat and maize (*Zea mays* L.), there is a vast range of environments to be considered. Bread and durum wheat occupy an estimated 200 million ha globally, being grown from sea level to over 3500 m asl, and from the equator to latitudes above 60° N in Canada, Europe, and Asia and below 40° S in the Southern Hemisphere. This diversity of production environments presents enormous challenges for institutes like CIMMYT that participate in wheat research intended to benefit the entire developing world. A thorough understanding of wheat environments is important for any crop research effort, but it is essential in efforts seeking global impacts. Application of geospatial tools, data and methods are becoming increasingly important as a means to assist in understanding and characterizing such diverse and complex systems and environments (Hodson *et al.* 1998; White *et al.* 2001a).

In the present brief review, wheat-based agricultural systems are used to illustrate how geospatial technologies are being applied in international agricultural research, drawing predominantly on activities undertaken by CIMMYT. The examples cover two broad areas, current wheat distribution (where wheat is actually grown) and wheat production environments (the conditions in which wheat grows, or might be grown), with more emphasis given to the latter. For wheat production environments, specific factors such as climate, soil, socio-economic conditions, and biotic stresses are considered. Future climatic scenarios are considered briefly to examine how wheat environments might change over the next 30–40 years. Advances and progress are emphasized, but limitations and areas for improvement also exist and are also reviewed. All of the examples seek to improve the understanding of the environments for which CIMMYT wheat scientists and their colleagues work, thereby strengthening targeting, priority setting, and decision-making.

CURRENT WHEAT DISTRIBUTION

Current estimates are that over 200 million ha are sown to wheat, with 0.9 of this being bread wheat and

the remaining 0.1 durum wheat (FAOSTAT 2005). In terms of human consumption, wheat is the most important crop after rice (*Oryza sativa* L.). Despite this importance, few if any public datasets for wheat distribution exist that are sufficiently quantitative and spatially disaggregated to allow effective priority setting and targeting below the national level. Individual countries, particularly OECD countries, do have disaggregated, accurate data on wheat production, e.g. USA and UK, but for many parts of the world only national or regional-level data are available and these are sparse and of varying reliability. Lack of such information regarding even the basic distribution of wheat seriously limits global or regional wheat planning and research.

Various efforts seek to close this information gap. The study by Leff *et al.* (2004) was one of the first major works to describe global distributions of major crops at sub-national scales. At CIMMYT, an initial effort was made to consolidate readily available sub-national agricultural census data relating to wheat and combined with expert knowledge to define production zones (Trethowan *et al.* 2005). Subsequently, FAO, IFPRI (International Food Policy Research Institute, Washington, DC), and the Centre for Sustainability and the Global Environment (SAGE, University of Wisconsin-Madison's Nelson Institute), assembled global agricultural census data at the second-order administrative level as part of the Agro-MAPS initiative (FAO 2005). The spatial analysis group at IFPRI is processing the Agro-MAPS data further and has developed a spatial methodology (You & Wood 2005) that allocates distributions of 20 major crops, including wheat, at a 5 arc min (approximately 9 km) grid cell size. The IFPRI method is based on a cross-entropy approach, which uses machine learning with stochastic sampling of multiple sources of information, including satellite imagery, biophysical crop suitability assessments, and population density. This approach is currently being evaluated at CIMMYT and other CGIAR centres.

WHEAT PRODUCTION ENVIRONMENTS

In the present review, a holistic view of wheat production environments is considered. The production environment is delimited by factors ranging from climate and soils to crop management (e.g. irrigation, tillage practices), social factors (e.g. farmer typology by gender, wealth or status) and biotic and abiotic stresses (e.g. pests, diseases or drought). These typically exhibit strong spatial patterns, hence are amenable to use and analysis with geospatial technologies.

Global wheat mega-environments (MEs)

Given the range and diversity of environments in which wheat is grown, an obvious need is to classify

wheat production areas in order to guide how priorities are established for allocating resources to plant breeding, agronomic research and technology promotion. At CIMMYT, the concept of MEs was first used to prioritize wheat improvement, starting in the late 1980s (Rajaram *et al.* 1994). The MEs represent global regions – not always geographically contiguous – with similar adaptation patterns, defined by crop production factors, consumer preferences, and wheat growth habits. Their current purpose is seen as assisting international priority setting, collaboration, and targeting of germplasm or agronomic practices to specific environments.

The criteria used to delimit the MEs have evolved over time. The initial criteria involved broad, generic definitions of key components such as moisture regimes and temperature ranges, e.g. 'high rainfall' v. 'low rainfall' or 'moderate cold' v. 'severe cold' (see Braun *et al.* 1996). More recently, availability of global datasets for agroclimatic parameters, e.g. WorldCLIM (Hijmans *et al.* 2005) and global irrigated area (Siebert *et al.* 2005), and advances in GIS tools that permit the efficient use and analysis of these datasets, have created opportunities to define and map wheat MEs based on more quantitative climate, soil, and management data. White *et al.* (2001*b*) initiated the process of applying GIS tools and datasets in order to revise and update the ME definitions being used by CIMMYT's wheat programme. The foundation for this work was the unique, extensive network of international wheat testing sites run by national agricultural research partners in collaboration with CIMMYT. Sites in the network (approximately 800) were geo-referenced and classified according to predominant ME by knowledgeable wheat scientists (Fig. 1). Subsequently, underlying climatic and edaphic factors were extracted and used to determine quantitative criteria for mapping the MEs. The contrasting criteria arising from the traditional and geospatial approaches for classifying spring wheat MEs are given in Table 1.

Long-term mean minimum temperature in the coolest quarter (three consecutive coolest months of the year) proved effective in distinguishing among the winter-grown spring, winter/facultative, and summer-grown spring wheats (Fig. 2). This temperature criterion was also useful for separating ME1 (favourable, irrigated) from ME5, where heat tolerance is required, with the upper limit of ME1 occurring at 11 °C. Using the criteria described above, it has been possible to delineate spatial distributions of the MEs and map them within a GIS. Selected ME zones for eastern Africa, the Middle East, and South Asia are shown in Fig. 3, where it is seen, for example, that the favourable, irrigated, ME1 environment occurs predominantly in Pakistan and India, but also is represented in the Middle East and Egypt.

Table 1. *CIMMYT spring wheat mega-environment (ME) definitions, using qualitative and geospatial criteria*

ME	Original criteria	Geospatial criteria
ME1	Favourable, irrigated, low rainfall	Coollest quarter (three consecutive coolest months) mean min temp $\geq 3^{\circ}\text{C}$ $< 11^{\circ}\text{C}$, plus $> 5\%$ of 5 arc min grid cell equipped for irrigation
ME2a	High rainfall. Highland summer rain	Wettest quarter (three consecutive wettest months) mean min temp $\geq 3^{\circ}\text{C}$ $< 16^{\circ}\text{C}$, wettest quarter precipitation $\geq 250\text{ mm}$, elevation $\geq 1400\text{ m}$
ME2b	High rainfall. Lowland winter rain	Coollest quarter mean min temp $\geq 3^{\circ}\text{C}$ $< 16^{\circ}\text{C}$, coolest quarter precipitation $\geq 150\text{ mm}$, elevation $< 1400\text{ m}$
ME3	High rainfall, acid soil	Climate criteria as for ME2 (a & b merged), topsoil pH < 5.2
ME4	Low rainfall	Coollest quarter mean min temp $\geq 3^{\circ}\text{C}$ $< 11^{\circ}\text{C}$, wettest quarter precipitation $\geq 100\text{ mm}$ $< 400\text{ mm}$
ME4c	Low rainfall, stored moisture	Coollest quarter mean min temp $\geq 3^{\circ}\text{C}$ $< 16^{\circ}\text{C}$, wettest quarter precipitation $\geq 100\text{ mm}$ $< 400\text{ mm}$
ME5	Warm, irrigated	Coollest quarter mean min temp $> 11^{\circ}\text{C}$ $< 16^{\circ}\text{C}$, plus $> 5\%$ of 5 arc min grid cell equipped for irrigation
ME6	High latitude ($> 45^{\circ}\text{ N}$ or S)	Coollest quarter mean min temp less than -13°C , warmest quarter mean min temp $\geq 9^{\circ}\text{C}$

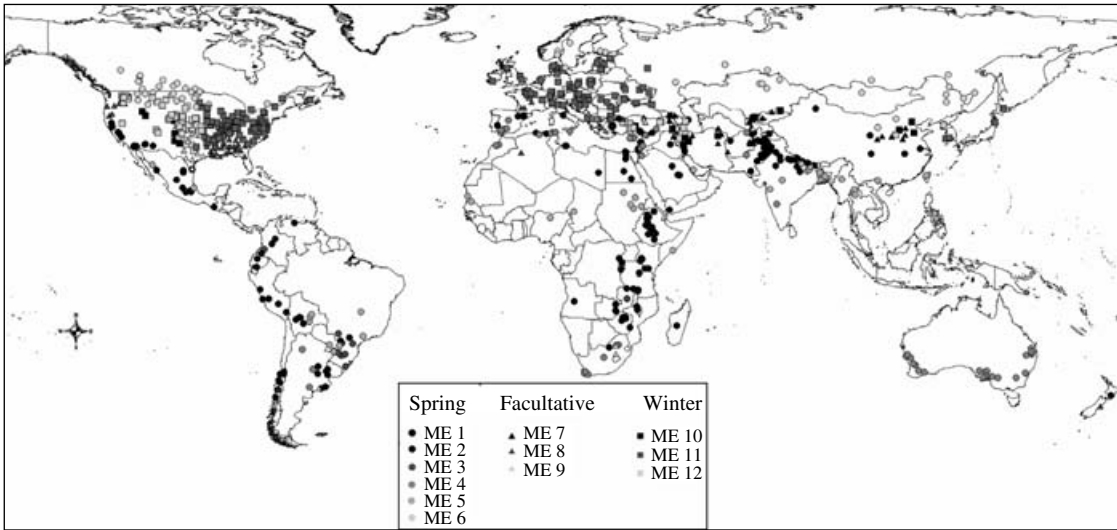


Fig. 1. Distribution of locations of wheat trials conducted by national agricultural research services and CIMMYT, classified by ME.

Separating facultative wheat environments from true winter wheat environments remains problematic. This is not entirely surprising. Wheats with facultative habits, by definition, occur in transition zones between spring and winter wheat regions, and the genetic basis of the class is uncertain (see Crofts 1989). Work is underway to apply cluster analysis on site-specific agroclimatic data to identify criteria that better distinguish among spring, facultative and winter wheat environments.

It is important to note that many of the insights arising from the work on characterizing MEs, and

likewise for other subsequent examples in the present review, were only possible due to the unique nature of spatial analysis methods. For example, essential inputs, e.g. climate surfaces, were only available as a result of the application of spatial interpolation techniques; environment classification was facilitated using analytic approaches such as location-based selection and spatial overlay that are readily applied in a GIS.

While these new approaches have improved our understanding of major wheat regions, the criteria assume static environmental conditions and thus

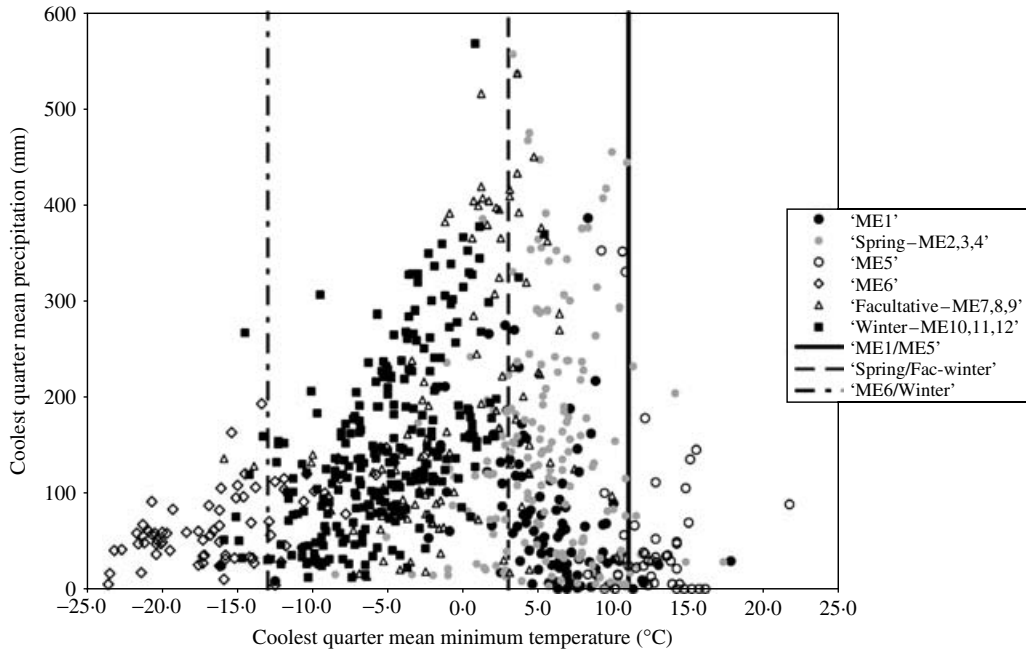


Fig. 2. Use of temperature criteria to further define wheat MEs.

ignore temporal variation due to year-to-year variation in climatic conditions. Trethowan *et al.* (2005) showed how specific locations may fluctuate between ME2 (high rainfall) and ME4 (low rainfall) depending on seasonal conditions. The issue of temporal variation and frequencies of occurrence is explored later.

Wheat MEs and climate change

Global climate change poses both threats and opportunities for agriculture. The third assessment report of the Inter-governmental Panel on Climate Change (IPCC 2001) concluded that 'The Earth's climate system has demonstrably changed on both global and regional scales since the pre-industrial era, with some of these changes attributable to human activities,' and also that 'Models of cereal crops indicate that in some temperate areas potential yields increase with small increases in temperature but decrease with larger temperature changes (medium to low confidence). In most tropical and subtropical regions, potential yields are projected to decrease for most projected increases in temperature (medium confidence).' Given the increasing body of supporting evidence, it is likely that global change will affect most wheat producing regions.

The more quantitative definitions ascribed to global wheat MEs (described in the previous section), coupled with spatially disaggregated scenarios for

future climates, offer opportunities to explore how future trends might affect global wheat environments. Ortiz *et al.* (in preparation) used one such scenario to redelineate wheat MEs. The climate change scenario used was described by Govindasamy *et al.* (2003) and assumed a doubling of CO₂ using the CCM3 climate model, CCM3 outputs were subsequently downscaled to a 30 arc-second resolution and published as part of the WorldCLIM dataset (Hijmans *et al.* 2005). Under projected trends in greenhouse gas production, this scenario roughly approximates conditions for year 2050. These revised climate-based wheat ME definitions revealed potential for important shifts in wheat environments. For example, in the Indo-Gangetic Plains of South Asia, large regions of favourable, high potential ME1 were predicted to become heat-stressed, lower potential ME5 (Ortiz *et al.* in preparation). This area is one of the world's breadbaskets, accounting for around 0.14–0.15 of global wheat production and supporting over 0.5 billion people – many of whom are highly dependent on wheat (Fig. 4). Assuming current population levels, this change would result in an additional 200 million people residing in areas where wheat production would be affected by heat stress.

A first step has been taken in relating climate change to wheat environments and additional factors should be considered in future work. Potential improvements for future work might include the incorporation of additional climate scenarios,

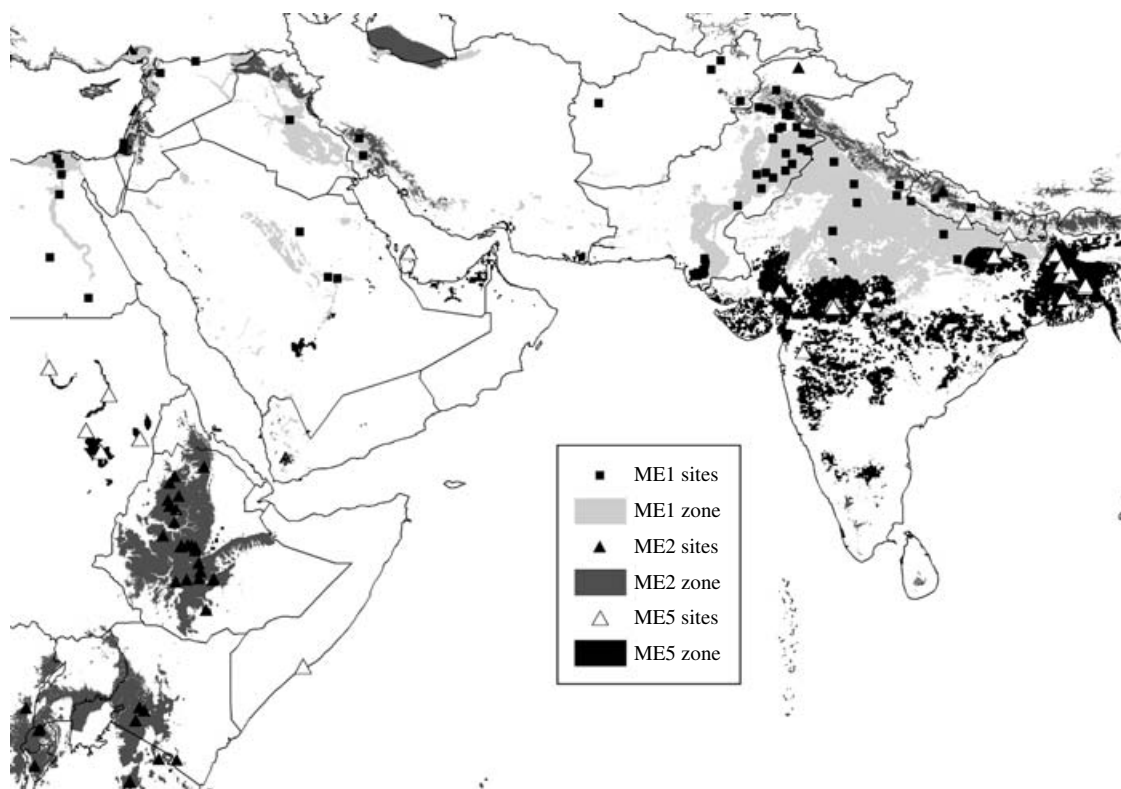


Fig. 3. Example wheat ME zonation map for selected spring wheat environments in eastern Africa, the Middle East and South Asia.

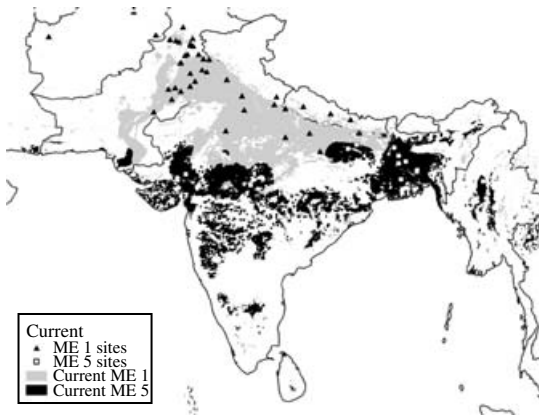
assumptions on likely changes in irrigation patterns and adaptive changes in cultivars or crop management practices. However, the study highlighted trends that merit more in-depth research to assist wheat programmes with planning for climate change.

Biotic stress and wheat production environments

Pest and disease and disease management is another topic for which spatial information can enhance planning and research. The potential spread of a new *Sr31*-virulent wheat stem rust (*Puccinia graminis* Pers.) race Ug99 is illustrative. This race arose in East Africa (Pretorius *et al.* 2000) and presents a major threat to wheat producing regions from Africa to China (CIMMYT 2005). For more than 30 years, sources of stem rust resistance, such as the *Sr31* and *Sr38* loci, provided effective protection against stem rust, forming the resistance-base for a large proportion of the world's wheat cultivars. Unfortunately, Ug99 is not controlled by these sources (Wanyera *et al.* 2006). This threat thus poses an urgent need to assess the potential risk to wheat regions of Africa,

the Middle East, and Asia. Wheat rusts (*Puccinia* spp.) are obligate pathogens that rely on the production of huge numbers of urediniospores and subsequent wind dispersion for transmission onto new susceptible hosts. Given the inherently spatial nature of Ug99 migration, GIS tools are starting to be used as a framework to integrate relevant factors determining likely movement (Hodson *et al.* 2005). First, current status and distribution of Ug99 in East Africa were incorporated into a spatial database and mapped. A predicted migration route and subsequent potential risk zone were then delimited using historical evidence of previous rust epidemics originating in East Africa, prevailing winds, optimal climatic conditions, and wheat distributions. This process identified a potential risk zone for infection by Ug99, assuming natural wind-borne dispersal, that covered the major wheat growing areas of East Africa and the Nile Valley, the Middle East as far north as southern Turkey and eastward across the entire Indo-Gangetic Plains. Within this zone, existing data on varietal susceptibility revealed that the vast majority of cultivars are either completely susceptible to Ug99 or their susceptibility level is unknown due to lack of testing

(a) Current



(b) Future

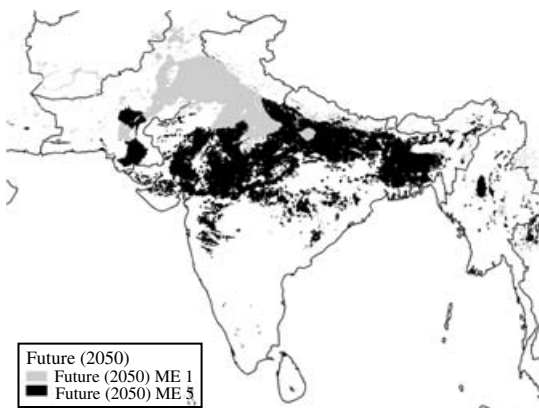


Fig. 4. Principal wheat ME zones (ME1 – high potential, favourable, irrigated; ME5 – heat-stressed, lower potential) in South Asia under (a) current climatic conditions, and (b) future climatic scenarios (a doubling of CO₂ levels, roughly equating to year 2050).

(Fig. 5). Of the reported 44 million ha planted to known cultivars, less than 0.01 of this area proved to have been planted with cultivars showing even moderate resistance to Ug99. Availability of spatially disaggregated wheat production data, in combination with germplasm susceptibility data and demographic data, permitted scenarios for potential loss to be developed that included production losses, economic losses, and farming population impacts. If an Ug99 epidemic occurs, the consequences for global food security may be catastrophic.

The study of Hodson *et al.* (2005) is perhaps the first to assess likely Ug99 movements using quantitative data, and supports the hypothesis of Singh *et al.* (2004) that east Africa and the wheat area of Asia

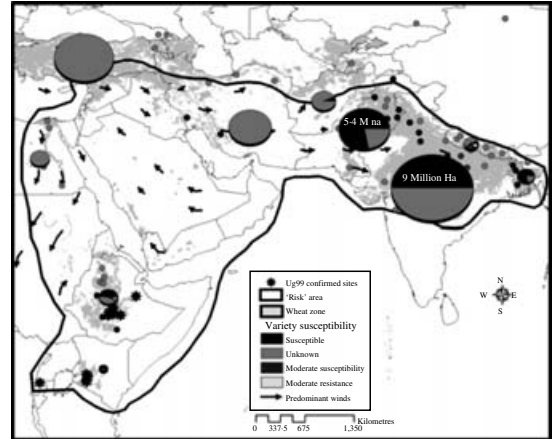


Fig. 5. Initial, potential risk zone for stem rust race Ug99 under natural migration conditions. Wheat variety susceptibility, based on reported areas planted, is indicated. Symbols are sized proportional to reported area planted.

may comprise a single epidemiologic zone. However, given the rising concern over the emergence and spread of Ug99 there is a clear need for more detailed spatial modelling of the new race. Predicted patterns of movement of air-borne pathogens are filled with uncertainty, although advances in air-borne spatial modelling and prediction offer interesting insights (APHIS 2004) on likely paths of spread, probability of infection and decision support for control measures. Such information can guide establishment of systems for accurate monitoring and early warning as well as decisions on how to minimize the spread of the disease and alleviate its impact.

Traditional, field-based pest/disease surveys are another area in which geospatial technologies are playing an increasingly important role. GPS technology has revolutionized location-based data collection in the field, making data collection rapid, accurate and simple. Subsequent analysis within a GIS framework can add considerable value and provide new insights. Cereal nematode and soil pathogen surveys in wheat areas of Turkey provide one example of the growing role of geospatial technologies in pest/disease surveys (A. F. Yýldýrým, personal communication). In these surveys, all collection sites were geo-referenced using GPS in the field, and geospatial statistics applied. This approach permitted the identification of areas with significant clusters of high or low incidence of particular nematode species, plus subsequent combination and correlation with important secondary spatial data (soil properties data in this instance). Use of geospatial technologies in this manner enriches and adds value to traditional surveys.

Socio-economic factors and wheat production environments

Efficient decision-making in agricultural development usually requires considering many factors beyond the basic agroclimatic and edaphic conditions. Often, socio-economic data, especially indicators of welfare or poverty, are also major concerns. Data availability and quality in this thematic area can be problematic, although substantial progress is being made in both methodologies and coverage for mapping socio-economic status (e.g. CIESIN 2006).

Poverty mapping, the spatial representation and analysis of indicators of human well-being and poverty, has become an increasingly important instrument for policymakers, planners, researchers, and other development workers (e.g. Henninger & Snel 2000). Poverty is a spatially heterogeneous phenomenon and effective targeting of interventions to reduce poverty requires understanding what factors drive local or regional incidence of poverty. Poverty mapping has benefited from three technical advances: increased availability of relevant data, development of GIS, and improved econometric techniques such as small area estimation (Bigman & Fofack 2000). These advances have led to a rapid expansion in the availability of disaggregated poverty maps, currently covering more than 25 developing countries (CIESIN 2006). Geographic targeting to the level of small administrative areas improves cost effectiveness of development spending and is more efficient at reaching the poor or bypassed areas (e.g. Elbers *et al.* 2004). Agricultural research unquestionably has alleviated poverty (Evenson & Gollin 2003), but many regions with large numbers of rural poor have been largely bypassed. Bellon *et al.* (2005) proposed that incorporation of poverty mapping techniques, in parallel with more traditional biophysical environmental characterizations, should improve the likelihood that agricultural research will benefit rural poor. Accordingly, the study of Bellon *et al.* (2005) combined CIMMYT maize MEs (Setimela *et al.* 2005) with high-resolution rural poverty maps in Mexico, resulting in improved information on target zones for specific technology interventions (Fig. 6). The derived framework has been subsequently applied as a tool to assist in the targeting of specific small-scale maize improvement technologies such as 'targeted allele introgression' described by Bergvinson & Garcia-Lara (2004). At present, similar work has not been undertaken for wheat, but the approach appears applicable for many wheat regions.

FUTURE DIRECTIONS

Although spatial characterization of wheat environments has proven utility, much greater impact is expected as we advance beyond static definitions of

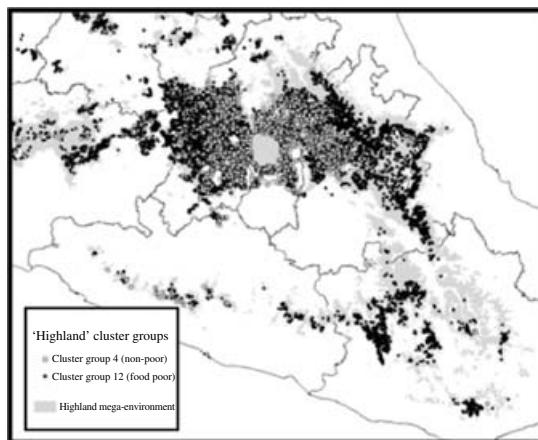


Fig. 6. Example of two contrasting cluster groups of rural communities (G4 and G12) in terms of poverty, occurring within a relatively homogeneous environment in Central Mexico, shown in relation to the independently derived CIMMYT highland maize ME (from Bellon *et al.* 2005).

environments and incorporate temporal variation. The best example of this promise is from characterization of target population environments (TPE), by coupling crop simulation models with long-term weather records to determine seasonal sequences of stress over many years. The stress patterns are subsequently analysed to determine frequencies of specific environment types (Chapman *et al.* 2000a; Löffler *et al.* 2005). The resulting information is then used to weight data from series of multi-environment trials according to how representative they are of the TPE, and so improve selection efficiency (Chapman *et al.* 2000b).

The greatest current constraint to coupling simulation models with spatial analysis is limited geographic coverage of daily weather records. Recent advances in remotely sensed climatic data products offer potential gains for advancing $G \times E$ interaction studies. Daily (and decadal) rainfall estimates, based on remotely sensed cold cloud temperature data, are now available for Africa via the USGS FEWS Net activities. In addition, NASA now provides global 3-h rainfall estimates through the Tropical Rainfall Monitoring Mission (TRMM) programme at a spatial resolution of 0.25° . A wider range of daily climatic variables are also being provided at a coarser spatial resolution (1° grid) through the Climatology Resource for Agroclimatology programme (Chandler *et al.* 2004). These data are available in a format suitable for crop models, and efforts are underway to evaluate whether the coarse spatial scale limits their utility as inputs to crop simulation models. It should be noted that private sector efforts to characterize dynamic US maize environments already use

remotely sensed rainfall data to classify multi-environment trials (Löffler *et al.* 2005).

The climatic datasets described above may also have utility as inputs into predictive crop disease models. The predictive model for *Fusarium* head blight developed by Pennsylvania State University and partners (available at <http://www.wheatscab.psu.edu/>) illustrates this potential. The model, developed for the USA, is driven through easy access to extensive sources of near-real-time meteorological station data. The increasing availability of remotely sensed climatic data opens up the possibility of developing similar models for data-sparse regions in developing countries.

CONCLUSIONS

Spatial technologies, such as GIS, GPS and remote sensing, are finding application in an ever expanding range of thematic areas, and this trend is likely to continue in future. Wheat research at CIMMYT provides just one set of examples of these advances. Improvements in quality and availability of spatial data combined with rapidly improving analytical tool advances are increasing our capability to use spatial technologies to improve decision-making, planning, and targeting. Numerous aspects of wheat research have benefited from the use of these technologies – an improved understanding of wheat production areas and environments at global and local scales, insights into potential shifts in production environments with changing climate, and exploration of the potential spread of disease epidemics. It is important to note that most of the insights gained in these diverse studies were only possible as a result of the unique nature of spatial analysis methods, e.g. spatial interpolation, spatial overlay, location-based selection, and space–time visual analysis. In the absence of spatial analysis, it is unlikely that similar insights or advances could have been achieved.

Perhaps the greatest opportunities are found in advancing beyond static definitions of environments and incorporating temporal variability to estimate the probability or frequency of occurrence of different environment types. Increased availability of nearly real-time daily weather data derived from remote sensing may further improve characterization of environments and permit regional-scale modelling of dynamic processes, such as disease progression or crop water balance.

Similarly, advances in the precision and spatial resolution of future climate and global circulation models are likely to result in improved abilities to predict and model likely changes in crop production environments. Improvements in this area are likely to have major impacts in influencing planning and policy decisions of global crop breeding programmes

in terms of target areas, traits and management practices within a changing world.

Despite many advances, use of geospatial technologies is less widespread than it could be within the international agricultural research community and partner organizations. Limits to wider adoption are multi-faceted and often vary depending on specific circumstances, so are not easy to characterize. Important limiting factors often include: data availability at an appropriate geographic scale; awareness amongst researchers; reluctance to explore non-traditional technologies; training; access to software tools; and in some developing countries access to computers.

Another area of concern is that the outputs of geospatial analyses often are visually impressive products whose accuracy, nonetheless, is difficult to assess. Few maps include indicators of accuracy or expected reliability. This problem reflects the fact that geospatial techniques are essentially used to create complex models. Thus, hypothesis testing in geospatial analysis is analogous to the problems of identifying testable hypotheses in outputs of simulation models.

A map of wheat MEs (e.g. Fig. 3), can be viewed as the hypothesis that because different wheat genotypes respond differently to day length, temperature and water management, genotype \times environment interactions for grain yield are reduced if environments are grouped using the described criteria. While this hypothesis could be tested by examining the portion of variance attributable to MEs in an analysis of variance for a multilocation trial, problems arise in identifying a suitable set of test data. Even at a centre such as CIMMYT, yield trials usually are targeted to subsets of the MEs and include genotypes pre-selected for expected low $G \times E$ within those environments. These difficulties do not excuse GIS from conventional scientific scrutiny but indicate the problems inherent in its use.

An additional challenge, especially in times of resource scarcity, is institutional priority setting. For the projections on the spread of the rust race Ug99, the predicted epidemic may, regrettably, prove self-evident. However, a much better understanding of the utility of the modelling effort requires a major monitoring effort over coming years. Proposals have been forwarded for this work but understandably this work is viewed as secondary in relation to identifying and distributing resistant germplasm. These examples are indicative of some of the major challenges for scientists who wish to apply geospatial techniques.

Diverse examples of applications of geospatial technologies within international agricultural research have been highlighted in this review. Given the increasing awareness and application amongst researchers, spatial technologies will undoubtedly see increasing use throughout the agricultural research and development process.

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